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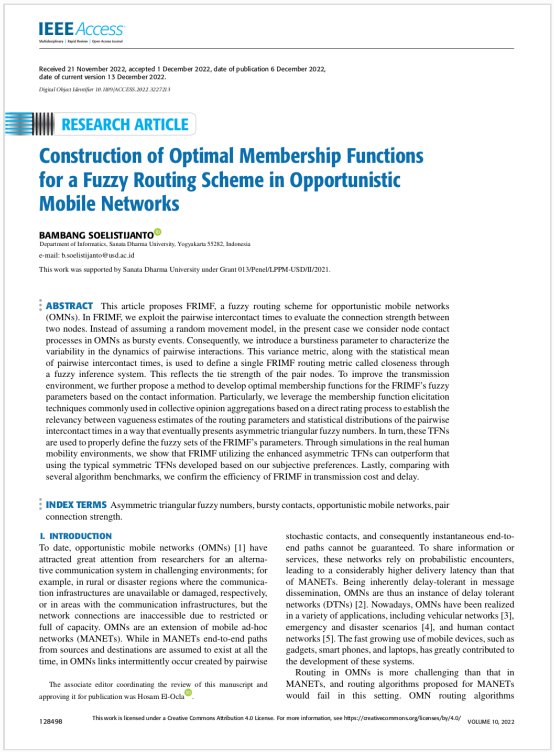
File size:	1.32M
Page count:	16
Word count:	11,458
Character count:	61,009
Submission date:	09-Jan-2023 01:05PM (UTC+0700)
Submission ID:	1990062791



IEEE Access

Received 21 November 2022, accepted 1 December 2022, date of publication 6 December 2022, date of current version 15 December 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3227213

RESEARCH ARTICLE

Construction of Optimal Membership Functions for a Fuzzy Routing Scheme in Opportunistic Mobile Networks

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This work was supported by Sanata Dharma University under Grant 013/Penel/LPPM-USD/II/2021.

ABSTRACT This article proposes FRIMF, a fuzzy routing scheme for opportunistic mobile networks (OMNs). In FRIMF, we exploit the pairwise intercontact times to evaluate the connection strength between two nodes. Instead of assuming a random movement model, in the present case we consider node contact processes in OMNs as bursty events. Consequently, we introduce a burstiness parameter to characterize the variability in the dynamics of pairwise interactions. This variance metric, along with the statistical mean of pairwise intercontact times, is used to define a single FRIMF routing metric called closeness through a fuzzy inference system. This reflects the tie strength of the pair nodes. To improve the transmission environment, we further propose a method to develop optimal membership functions for the FRIMF's fuzzy parameters based on the contact information. Particularly, we leverage the membership function elicitation techniques commonly used in collective opinion aggregations based on a direct rating process to establish the relevancy between vagueness estimates of the routing parameters and statistical distributions of the pairwise intercontact times in a way that eventually presents asymmetric triangular fuzzy numbers. In turn, these TFNs are used to properly define the fuzzy sets of the FRIMF's parameters. Through simulations in the real human mobility environments, we show that FRIMF utilizing the enhanced asymmetric TFNs can outperform that using the typical symmetric TFNs developed based on our subjective preferences. Lastly, comparing with several algorithm benchmarks, we confirm the efficiency of FRIMF in transmission cost and delay.

INDEX TERMS Asymmetric triangular fuzzy numbers, bursty contacts, opportunistic mobile networks, pair connection strength.

I. INTRODUCTION

To date, opportunistic mobile networks (OMNs) [1] have attracted great attention from researchers for an alternative communication system in challenging environments; for example, in rural or disaster regions where the communication infrastructures are unavailable or damaged, respectively, or in areas with the communication infrastructures, but the network connections are inaccessible due to restricted or full of capacity. OMNs are an extension of mobile ad-hoc networks (MANETs). While in MANETs end-to-end paths from sources and destinations are assumed to exist at all the time, in OMNs links intermittently occur created by pairwise stochastic contacts, and consequently instantaneous end-to-end paths cannot be guaranteed. To share information or services, these networks rely on probabilistic encounters, leading to a considerably higher delivery latency than that of MANETs. Being inherently delay-tolerant in message dissemination, OMNs are thus an instance of delay tolerant networks (DTNs) [2]. Nowadays, OMNs have been realized in a variety of applications, including vehicular networks [3], emergency and disaster scenarios [4], and human contact networks [5]. The fast growing use of mobile devices, such as gadgets, smart phones, and laptops, has greatly contributed to the development of these systems.

Routing in OMNs is more challenging than that in MANETs, and routing algorithms proposed for MANETs would fail in this setting. OMN routing algorithms

The associate editor coordinating the review of this manuscript and approving it for publication was Hosam El-Ocla.

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by Soelistijanto Bambang

Submission date: 09-Jan-2023 01:05PM (UTC+0700)
Submission ID: 1990062791
File name: for_a_Fuzzy_Routing_Scheme_in_Opportunistic_Mobile_Networks.pdf (1.32M)
Word count: 11458
Character count: 61009

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 21 November 2022, accepted 1 December 2022, date of publication 6 December 2022,
date of current version 13 December 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3227213

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ABSTRACT This article proposes FRIMF, a fuzzy routing scheme for opportunistic mobile networks (OMNs). In FRIMF, we exploit the pairwise intercontact times to evaluate the connection strength between two nodes. Instead of assuming a random movement model, in the present case we consider node contact processes in OMNs as bursty events. Consequently, we introduce a burstiness parameter to characterize the variability in the dynamics of pairwise interactions. This variance metric, along with the statistical mean of pairwise intercontact times, is used to define a single FRIMF routing metric called closeness through a fuzzy inference system. This reflects the tie strength of the pair nodes. To improve the transmission environment, we further propose a method to develop optimal membership functions for the FRIMF's fuzzy parameters based on the contact information. Particularly, we leverage the membership function elicitation techniques commonly used in collective opinion aggregations based on a direct rating process to establish the relevancy between vagueness estimates of the routing parameters and statistical distributions of the pairwise intercontact times in a way that eventually presents asymmetric triangular fuzzy numbers. In turn, these TFNs are used to properly define the fuzzy sets of the FRIMF's parameters. Through simulations in the real human mobility environments, we show that FRIMF utilizing the enhanced asymmetric TFNs can outperform that using the typical symmetric TFNs developed based on our subjective preferences. Lastly, comparing with several algorithm benchmarks, we confirm the efficiency of FRIMF in transmission cost and delay.

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Routing in OMNs is more challenging than that in MANETs, and routing algorithms proposed for MANETs would fail in this setting. OMN routing algorithms

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completely modify the paradigm of routing in MANETs to enable message delivery with the nonexistence of stable paths between sources and destinations. The algorithms deliver messages to the destinations over a sequence of contact events. Nonetheless, the multi-hop forwarding over such intermittently-connected networks possesses some challenges: the dynamic changes of the network's topology, the long delay to obtain the network's state data, and the cost of flooding of this global information, imply that routing algorithms for conventional networks, e.g., the Internet and MANETs, that rely on global knowledge are suboptimal and costly. Instead, routing algorithms for OMNs may use either a naïve approach (by increasing message replicas distributed in the network) or a heuristic approach (by estimating a pairwise contact probability based on the node's locally available information).

OMNs are commonly modelled as a time-varying graph $G = (V, E)$, since both the edges E and the states of vertices V continuously vary in time. When two nodes come into contact, the link is established between them, and they are able to exchange messages. Understanding the characteristics of pair connections is therefore beneficial for message transfers in OMNs. A link prediction between OMN nodes is commonly calculated based on various contact metrics, such as contact times, contact frequency, or intercontact times. The study in [6], [7] revealed that real objects' meetings exhibit a repetitive pattern to some extent. Yet, some studies simply assumed a random *i.i.d.* (independent-identically-distributed) model for contact processes in OMNs [8]. However, [9], [10] showed that the pairwise intermeeting time patterns in real human mobility cases fit power-law distributions better than exponential ones. Goh and Barabási [11] argued that the dynamics of real systems, such as earthquake patterns, gene expression, and human behaviours, exhibit a bursty, intermittent nature. The authors furthermore identified two distinct processes that lead to the burstiness, namely memory and interevent time distribution. While the memory has a substantial impact on the burstiness of natural events, e.g., earthquakes and weather patterns, the burstiness of human dynamics is mostly caused by changes in the interevent time distribution.

In this research, we focus on *human-centric* OMNs, also referred to as *mobile social networks* (MSNs) [12], where people's mobility is impacted by their social relationships, such as in daily activities at campus or the workplace, or in temporary events, e.g., conferences or seminars. From [11], we can assume that the contact patterns in such OMNs possess a bursty nature. We characterize the burstiness of node meetings based on the dynamics in pairwise intercontact time distribution. The distribution of pairwise intercontact times has been thoroughly studied under different mobility models in several papers [13], [14]. Moreover, the authors of [15] argued that the statistical mean and variance of pairwise intercontact times can comprehensively measure the ability of a link to exchange information between nodes. In this paper, we introduce a *burstiness parameter* [11] to measure the variation of pairwise intercontact times between OMN nodes. Using this variance metric along with the mean of pairwise intercontact times, we develop a single routing metric called *closeness* through a fuzzy inference system [16]. This parameter weighs the connection strength between a pair of nodes. According to the hill-climbing heuristic search [17], the proposed routing algorithm FRIMF suggests that a message will be transmitted to future relays with the closeness value to the destination is higher than that of the current node.

To improve the transmission environment, we further propose a method to construct optimal membership functions for the FRIMF's fuzzy parameters. Defining membership functions is one of the most essential tasks when evaluating systems or solving problems using fuzzy logic. Membership functions are used to define fuzzy sets of the inputs of a fuzzy inference system. Obviously, a more precisely defined membership function leads to a more accurate output or a more efficient fuzzy analysis system. From the literature, methodologies to develop membership functions can be based on *subjective* or *objective* information [18], [19]. In the former case, the subjective opinion of experts is commonly used in the analysis of uncertainty of events. In the latter case, membership functions are defined based on statistical distributions of the observed data.

To date, numerous fuzzy routing schemes have been proposed for OMNs [20], [21], [22], [23], [24]. However, none of them considers statistical distributions of the routing parameters when defining the membership functions. Instead, the algorithms typically rely on the authors' assumptions or estimations when analyzing the vagueness of the routing metrics. This paper, in contrast, discusses a method to develop membership functions of the FRIMF's routing parameters based on statistical distributions of the pairwise intercontact times. To our best knowledge, FRIMF is the first OMN fuzzy routing algorithm that takes into account the encounter information when determining the membership functions of the routing metrics. Furthermore, we leverage the membership function elicitation methods typically used in collective opinion aggregations based on a direct rating process, e.g., in [25] and [26], to establish the relevancy between vagueness estimates of the routing parameters and statistical distributions of the pairwise intercontact times. This eventually results in *asymmetric triangular fuzzy numbers* (TFNs), which in turn are used to properly define the fuzzy sets of the FRIMF's routing parameters. Finally, our contributions in this paper are summarized as follows:

- We introduce a concise, yet comprehensive closeness metric to abstract the relationship between a pair of nodes. This measure is derived from the burstiness variation and the mean of pairwise intercontact times through a fuzzy inference system.
- To improve the transmission environment, we develop optimal membership functions for the FRIMF's fuzzy parameters based on the statistical distributions of pairwise intercontact times. We leverage the membership function elicitation strategies employed in group opinion

aggregations based on a grading process in [25] and [26] to produce asymmetric TFNs.

- According to the hill-climbing heuristic search [17], the proposed algorithm FRIMF (**F**uzzy **R**outing with **I**mproved **M**embership **F**unctions) forwards messages to future relays with a higher closeness value to the destination than that of the current carrier.
- In accordance with the simulation results in the ONE environment [27] and real human mobility scenarios, FRIMF using the improved asymmetric TFNs can outperform that utilizing the typical symmetric ones defined based on our subjective preferences. Finally, FRIMF enhances performances on delivery cost and latency of some given algorithm benchmarks.

The rest of the paper is structured as follows: a brief introduction to the related literature is given in Section II; FRIMF is proposed and analyzed in Section III; simulation results are presented and discussed in Section IV; and finally, Section V concludes the paper.

II. RELATED WORKS

A. PAIRWISE INTERCONTACT TIME DISTRIBUTIONS IN OMNs

Early works in OMNs used a simple random walk model to define node movements [8]. However, recent studies reveal that this random model is not realistic in real mobility cases. The authors of [6] and [7] argued that real object movements show a repetitive pattern to some extent. On the other hand, the authors of [11] and [28] observed that the dynamics of most real systems, such as weather and earthquake patterns, human behaviours, and user queries to a web search engine, exhibit a bursty, intermittent nature, characterized by intense activities over short periods of time followed by reduced or no activity over long periods of time. Two different processes lead to burstiness in the real-life settings: memory and interevent time distribution [11]. While memory is more dominant in the burstiness in natural phenomena, for human dynamics the bursty character is mainly due to the variations in the distribution of interevent times. Furthermore, the authors of [9] and [10] revealed that pairwise intercontact time distributions in human contact networks tend to fit log-normal distributions better than exponential ones, asserting the heterogeneity of contacts across any pair of nodes.

Until now, there has been a growing interest in understanding the distribution of pairwise intercontact times in OMNs. The distribution of pairwise intercontact times have been thoroughly studied under different realistic mobility models [13], [14]. Several routing algorithms proposed for OMNs have exploited pairwise intercontact time distributions when choosing better message carriers [15], [29], [30]. The authors of [15] argued that properly identifying the distribution of pairwise intercontact times can help to improve message transfers between a pair of nodes. In addition, [29] and [30] showed that intercontact times can outperform both duration and frequency of contacts in identifying the dynamics of node encounters in human contact networks. Furthermore, [15] and [29] proposed the mean of intercontact times as a comprehensive metric to evaluate a pair connection strength, since it can reflect both the duration and frequency of the contacts. In this paper, we introduce a closeness metric derived from the mean and variance of pairwise intercontact times through a fuzzy inference system to evaluate the connection strength between OMN nodes. Here, a burstiness metric [11] is considered to assess the variation of pairwise intercontact time distributions.

B. PROBABILISTIC ROUTING VS. FUZZY ROUTING ALGORITHMS

In typical probabilistic routing schemes, a delivery predictability metric is established based on the historical encounters between a pair of nodes to indicate how likely a future contact will occur between them. Clearly, a higher delivery predictability of the two nodes indicates a better chance between them to meet and exchange messages. A message is replicated to the encountered node whenever the node's delivery predictability to the destination is higher than that of the carrier node (Prophet [31]), or when it is higher than a given threshold (FairRoute [32]). By doing so, the algorithms can achieve a high delivery ratio as well as satisfying a low delivery cost. Nonetheless, such forwarding strategies may impose two potential issues, as follows. Firstly, the algorithms may result in a high message redundancy. For instance, Prophet always transfers a replica to the encountered node even though its delivery predictability (to the destination D) is only slightly higher than that of the current carrier. Secondly, on the contrary, the algorithms may cause the diffusion speed of replicas in the network relatively slow. For example, FairRoute suggests that the nodes having a delivery predictability higher than 0.5 are considered as good relays. Consequently, node A with the delivery predictability $P_{AD} = 0.53$ will be chosen as a good relay, but not for the case of node B with $P_{BD} = 0.48$. The decision-making problems emerge in these two cases that because node preferences (as optimal relays) are defined by utilizing either exact numbers or crisp thresholds. Due to the uncertainty of information or lack of complete knowledge, it is hard for the OMN routing algorithms to express their preferences towards the encountered nodes based on precise values or crisp boundaries. Alternatively, it is easier for the algorithms to use fuzzy terms (linguistic labels) to describe node preferences.

To date, a number of routing algorithms based on fuzzy logic have been proposed for OMNs [20], [21], [22], [23], [24]. In [23], routing metrics, namely distance, neighbour quantity, and relative velocity, were evaluated in four linguistic variables (TFNs) to select good relays in VDTNs. PaSS [24] uses node similarity metrics, both position and social similarities, and applies a fuzzy inference system to choose optimal message carriers. Similarly, FCNS [22] determines node preferences through fuzzy inference of social and mobile similarities. Wu et al. [20] proposed FDQLR

that combines fuzzy logic with the Q-learning algorithm to search the best route to the destination. Here, we introduce a closeness metric deduced from the fuzzy sets of the mean and variance of pairwise intercontact times to select optimal relays to the message destination. Furthermore, to enhance the routing performance, we propose a method to properly define the membership functions of the FRIMF's routing parameters based on statistical distributions of the intercontact times. Nevertheless, none of the abovementioned fuzzy routing schemes considered statistical distributions of the routing parameters when constructing the membership functions. Instead, the related works typically relied on the authors' subjectivities when performing such tasks.

C. MEMBERSHIP FUNCTION ELICITATION METHODS

Since the introduction of fuzzy sets [16], one of the main issues has been with the determination of membership functions. While in classical sets category membership is merely a yes-or-no choice, in fuzzy sets the idea of graded membership is considered when defining membership in a set. A membership function is used to assign a membership value to a fuzzy variable. The membership function essentially captures all fuzziness for a fuzzy set, and consequently a fuzzy set is entirely characterized by the membership function. Because of their importance, the development of these functions has received a lot of attention from the researchers. A number of methods for eliciting membership functions have been put out so far. Ross [18] introduced direct methods to construct membership functions, such as those based on intuition, inference, rank ordering, and inductive reasoning. The authors of [19], [33] discussed several practical techniques used in experiments with the aim of developing membership functions, e.g., polling, direct rating, interval estimation, and pairwise comparison. However, Dykhta et al. [34] proposed a method to build membership functions based on mathematical analysis in the fuzzy set theory.

In general, methodologies to elicit membership functions can be based on either subjective or objective information [18], [35], [36]. In the former case, experts' judgement is used in the analysis of uncertainty of an event. While this heuristic approach is simple, but it needs more knowledge or expertise in the particular area to produce optimal membership functions. On the other hand, a more rigorous technique to construct membership functions is based on statistical methods. This objective approach develops the membership function of a fuzzy set whose elements' features are statistically known. Specifically, this strategy transforms the probability distribution function into a possibility distribution function, which in turn is used to determine a fuzzy set of the objective information. The relations between possibility and probability theories have been broadly discussed in [37], [38], and [39]. Civanlar and Trussell [40] described the techniques for deriving optimal membership functions for some common probability density functions, such as uniform and Gaussian distribution functions. Yet, Pedrycz and Vukovich [36] combined the subjective opinions and the associated objective (experimental) data to construct the membership function of a fuzzy set. Tamaki et al. [41] proposed a strategy for identifying membership functions based on the fuzzy observation data. Methods for developing membership functions commonly used in the case of group opinion aggregations based on a direct rating process have been proposed in [25], [26], and [42]. In [42] the method generates a symmetric triangular fuzzy number (TFN), whose mode is given by the average opinion scores and the spread is determined by the maximum deviation of various scores from the mean point. In contrast, the strategies in [25] and [26] build an asymmetric TFN whose spread is calculated separately for the left and right sides based on the left and right score deviations from the average value, respectively. Finally, the studies in [43] and [44] emphasized the effectiveness of asymmetric TFNs compared with symmetric TFNs in fuzzy decision trees and fuzzy regression methods, respectively, for classification problems. In this paper, we utilize the strategies in [25] and [26] to develop asymmetric TFNs for the fuzzy sets of the FRIMF's routing parameters with reference to the statistical distributions of pairwise intercontact times.

III. SYSTEM MODEL DESIGN

Designing FRIMF comprises three main tasks: calculation of a closeness metric by the fuzzy inference system, development of a method to create optimal membership functions for the FRIMF's fuzzy parameters based on statistical contact data, and construction of the forwarding strategy of FRIMF.

A. CALCULATION OF A CLOSENESS METRIC USING THE FUZZY INFERENCE SYSTEM

One of the main issues of routing in OMNs is how to evaluate a link between a pair of nodes with intermittent

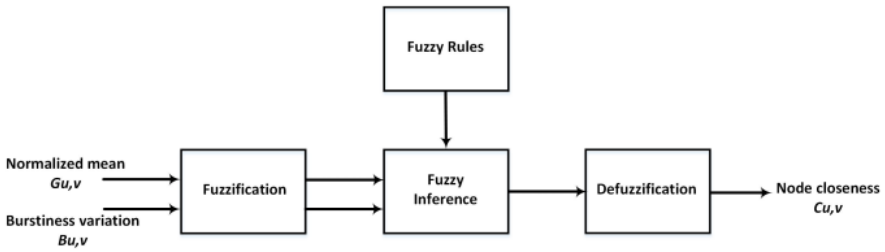

FIGURE 1. Block diagram of the fuzzy inference system of FRIMF routing.

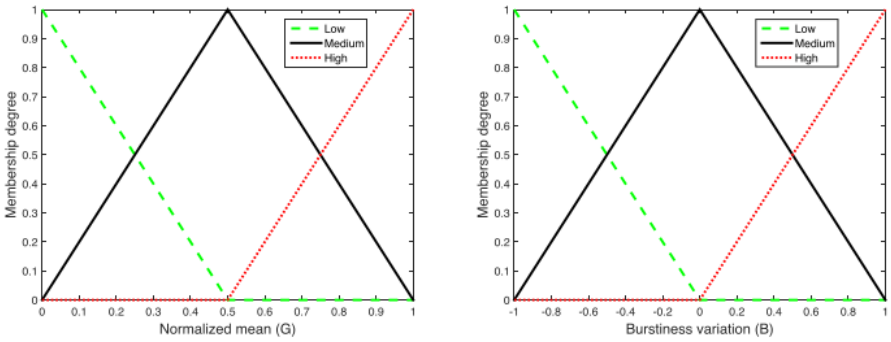

FIGURE 2. Symmetric TFNs of the FRIMF's fuzzy parameters: normalized mean (G) and burstiness variation (B).

connections. Possible candidates to measure the strength of a pair connection include contact times, contact frequency, and intercontact times. Classical routing algorithms typically rely on a single contact metric when selecting candidate relays [31], [32]. However, a contact metric may be ineffective to thoroughly describe the relations between two nodes. Recent routing schemes exploit several contact metrics when determining optimal relays [21], [22], [23]. Yet, considering multiple contact metrics on the routing decisions clearly increases the algorithm's complexity. In FRIMF, we condense the contact information between nodes u and v into a single closeness metric $C_{u,v}$ to comprehensively describe the connection strength between them. This metric is calculated based on the mean and variance of pairwise intercontact times. Furthermore, we hypothesize the contact processes in social-based OMNs possess a bursty nature. We introduce a burstiness parameter [11] to characterize the variation of pairwise intercontact time distributions, calculated as follows

$$B_{u,v} \equiv \frac{\left(\sigma_\tau / m_\tau - 1\right)}{\left(\sigma_\tau / m_\tau + 1\right)} = \frac{\left(\sigma_\tau - m_\tau\right)}{\left(\sigma_\tau + m_\tau\right)} \tag{1}$$

where m_τ and σ_τ are the average and standard deviation of intercontact times τ, respectively. $B_{u,v}$ has a value in the bounded range of $[1, -1]$, for "1" is the most bursty contact event, and "-1" is a perfectly regular contact event between the two nodes. Clearly, a lower $B_{u,v}$ is desirable since the two nodes can meet at a more regular interval, leading to a lower delay variation of information exchanges between them.

In addition to the burstiness metric, the second parameter required in the calculation of $C_{u,v}$ is the mean of pairwise intercontact times, m_τ. This statistical parameter represents the average waiting time of nodes u and v to meet in the future. We further normalize m_τ using the Gaussian similarity function [45] as follows

$$G_{u,v} = e^{-\left(\frac{m_\tau^2}{2s^2}\right)} \tag{2}$$

where s is a scaling parameter for intercontact times, and $G_{u,v}$ has a value in the range of $[0, 1]$. Obviously, a higher $G_{u,v}$ is more preferable for message delivery, since it indicates a higher probability that nodes u and v encounter in the near future, leading to a lower average transfer delay between them. Finally, we employ a fuzzy inference system to determine the degree of closeness between nodes u and v, $C_{u,v}$, based on two distinct input variables, namely the normalized mean $G_{u,v}$ and the burstiness variation $B_{u,v}$ of the pairwise intercontact times. Furthermore, we adopt the Mamdani fuzzy system [46] in this fuzzy system due to its widespread use in various fields. The FRIMF's fuzzy inference system consists of three main process blocks (as shown in Fig. 1): fuzzification, fuzzy inference, and defuzzification. In the following, we discuss the implementation of each component of the fuzzy evaluation system in detail.

1) FUZZIFICATION

In fuzzification, the values of inputs of the fuzzy system are converted to membership degrees of fuzzy sets using the membership functions. A membership function for a fuzzy variable x denoted $\mu(x)$ maps x to a value that quantifies the membership degree of x in a fuzzy set. In our fuzzification component, there are two distinct input variables: G and B, and for each variable we define three different fuzzy sets: *low*, *medium*, and *high*. As a consequence, we need to develop three distinct membership functions for these fuzzy sets. In the present case, we select triangular membership functions due to their low computation in mobile nodes. Additionally, we consider two different strategies to create the membership functions, namely a subjective and an objective method. In the former case, the triangular membership functions are developed based on our own preferences. For instance, in Fig. 2 (left) and (right) we show the membership functions that translate the values of the normalized mean G and the burstiness variation B, respectively, to membership degrees in three different classes of symmetric triangular fuzzy numbers (TFNs). Indeed, these membership functions are simple and straightforward, as they are defined without taking into account the statistical distributions of G and B. In the latter case, however, the membership functions of the FRIMF's fuzzy parameters are developed based on contact data (an objective approach). Particularly, we establish the relevancy between vagueness estimates of the FRIMF' parameters and statistical distributions of the

TABLE 1. Fuzzy inference rules.

Rules	*G*	*B*	→	*C*
1	*H*	*H*	→	*M*
2	*H*	*M*	→	*H*
3	*H*	*L*	→	*H*
4	*M*	*H*	→	*L*
5	*M*	*M*	→	*M*
6	*M*	*L*	→	*M*
7	*L*	*H*	→	*L*
8	*L*	*M*	→	*L*
9	*L*	*L*	→	*L*

pairwise intercontact times in a way that finally presents asymmetric triangular membership functions (we give the detail discussion of the proposed method in Section III.B).

2) FUZZY INFERENCE

The essence of fuzzy inference is determined by the fuzzy rules. We assume that a (encountered) node having a high normalized mean (G) and a low burstiness variation (B) with the destination is the best message carrier. Based on this assumption, the fuzzy *if-and-then* rules are developed, such as:

- *IF* normalized mean G is high *AND* burstiness variation B is low, *THEN* node closeness C is high.
- *IF* normalized mean G is medium *AND* burstiness variation B is medium, *THEN* node closeness C is medium.
- *IF* normalized mean G is low *AND* burstiness variation B is high, *THEN* node closeness C is low.

We list all 9 rules to enumerate all possible FRIMF's input conditions in Table 1. This rule set complies with our intuition towards the node closeness concept in OMNs when the mean and variance of pairwise intercontact times are considered. In the fuzzy inference process, we deduce all the rules in parallel and then combine all terms in the premise to determine the resulting membership. We use the *min-max* inference of the Mamdani fuzzy system, where the *AND* (minimization) and *OR* (maximization) operations are applied. In each rule, we use the fuzzy operator *AND* between two input variables (G, B), and the minimum of the two inputs' fuzzy weights is taken to define the support degree of the given rule in the cumulative fuzzy set. Subsequently, the aggregate operator (*OR*) is used that combines the results of all the rules into a single fuzzy set. Finally, the aggregated result is ready for defuzzification.

3) DEFUZZIFICATION

The final step of the fuzzy inference system is defuzzification. Defuzzification is a process of deducing the membership degrees of a fuzzy set into a crisp value. In this case, closeness C as the output of the FRIMF's fuzzy evaluation system has three grades: low, medium, and high. We use triangular membership functions for the fuzzy outputs as shown in Fig. 3. The final fuzzy output of closeness C is generated by defuzzifying from the aggregated result, taking the centre of area (centroid) of the superimposed membership curve. The final (crisp) value of $C*$ is computed as follows

$$C^* = \frac{\int C.\mu_{output}(C).dC}{\int \mu_{output}(C).dC} \tag{3}$$

where $\mu_{output}(C)$ represents a cumulative membership function aggregated from the outputs of the associated rules.

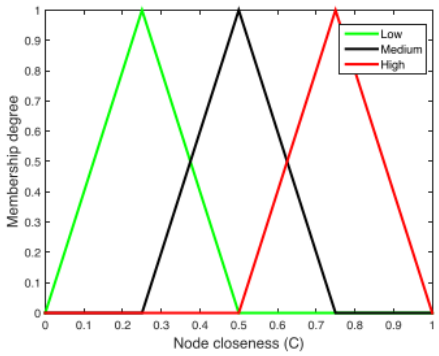

FIGURE 3. Membership functions of the FRIMF's fuzzy inference system output: node closeness (C).

B. DEVELOPMENT OF MEMBERSHIP FUNCTIONS BASED ON STATISTICAL DISTRIBUTIONS OF THE FUZZY VARIABLES

In this section, we discuss a technique to improve the typical symmetric triangular membership functions of the FRIMF's fuzzy parameters in Fig. 2. The identification of membership functions in this section is performed by the mathematical procedure that establishes the relations between a possibility distribution and a statistical distribution of the observed parameter. When both a probability and a possibility distribution deal with some kind of uncertainty and use the bounded interval of [0, 1] for their measures, they differ from each other in some sense. For instance, given the statement "Michael drinks X cups of coffee for his breakfast", a variable X can be related with both a probability and a possibility distribution in dissimilar interpretations as follows. The possibility distribution function $\pi_x(u)$ can be deduced as the degree of ease of Michael is able to drink x cups of coffee during his breakfast, but the probability distribution function $p_x(u)$ can be interpreted as the likelihood that he drinks x cups of coffee at breakfast by observing him for 100 days. Furthermore, from the possibility-probability consistency principle by Zadeh [16], an event that has a high degree of possibility does not necessarily have a high degree of probability as well, and an event that is impossible to occur certainly also improbable. Nevertheless, the consistency principle is not intended as an exact principle where the conversion between possibility and probability can be calculated precisely, but rather is a heuristic one that describes the principle relations between them. In general, the possibility distribution function $\pi_x(u)$ is determined to be numerically equal to the membership function $\mu_F(u)$ as

$$\forall u \in U, \quad \pi_x(u) \triangleq \mu_F(u) \tag{4}$$

In the present case, the (graded) possibility distribution of crisp values of a variable is represented by a triangular fuzzy number (TFN). A fuzzy number F is a fuzzy set defined on the real number and is characterized by a membership function $\mu_F : \Re \rightarrow [0, 1]$. It satisfies that F is normal, convex, and piecewise continuous. TFNs are a class of L-R fuzzy numbers with the membership function has a triangular form as follows

$$t(x; a, m, b) = \begin{cases} 1 - \dfrac{m - x}{m - a}, & a \le x \le m \\ 1 - \dfrac{x - m}{b - m}, & m \le x \le b \\ 0, & elsewhere \end{cases} \quad (5)$$

A TFN is generally represented as (a, m, b), where m denotes the mode, which is the most possible value of the fuzzy number ($\mu_F(m) = 1$), and a and b are the left and right endpoints, which indicate the left and right distances to the mode, respectively ($\mu_F(a) = \mu_F(b) = 0$).

We now propose a method to construct a TFN based on the strategies in [25] and [26] that aggregated the opinions of group members in a grading process. In those decision-making strategies, each individual in a group assessed a (surveyed) object in a predefined scale, and the collective opinion was finally obtained by aggregating the scores of all the group members. Due to the subjective divergence in the grading process, the individuals' opinions were therefore represented by a fuzzy number. Chang et al. [42] utilized a TFN in a grading process to study an ergonomic issue related to a video display terminal. A group of individuals were asked to observe the impacts of character size against viewing distance by proofreading passages displayed on the screen. The judgement scores were given by the participants, and eventually all the scores were converted to a TFN. In that case, the TFN was assumed to have a symmetric form, whose mode (m) was given by the mean of all the scores, and spreads (a, b) were simply defined by the maximum deviation from the mean value. However, the authors of [25] and [26] argued that the symmetric TFN is ineffective to detect the distribution of the judgement scores. Alternatively, an asymmetric TFN was chosen to improve the detection of the observed parameter distribution in the grading process.

In light of this, for each FRIMF's fuzzy system input we build an asymmetric TFN based on the strategies in [25] and [26] as follows. Initially, we transform the statistical distribution of (continuous) values of the FRIMF's input (G and B) into the frequency distribution of (discrete) crisp scores of a (surveyed) parameter in a predefined scale. As an example, in Table 2 we show a chart of the frequency distribution of the normalized mean G of a hypothetical contact dataset within a bounded range of [0, 1]. We initially define the range of values in each bin (in this case, of 0.1), and then count how many values fall into each interval. Subsequently, a crisp value x_i in each bin is determined that represents all the values within the given interval. Ultimately, we calculate the parameters required to construct an asymmetric TFN, namely mode (m), left spread (a), and right spread (b), based on the given frequency distribution of the crisp scores x_i, as follows.

At first, we discuss how to determine the mode of the TFN. Calculating the mode of a TFN involves finding the centre around which all x_i gather. Moreover, the ordinary methods, e.g., in [26] and [42], that consider statistical data to generate TFNs simply use the average value to define the mode value. Alternatively, we use the weight determination technique of [25] in the estimation process and take into account the frequency distribution of scores x_i to calculate the mode of the TFN, as follows. To estimate the centre of x_i, the pairwise relative distances between any values of x_i are calculated. Afterwards, the pairwise relative distance matrix $\mathbf{D} = [d_{ij}]_{n \times n}$ is established with $d_{ij} = |x_i - x_j|$, and thus $d_{ij} = d_{ji}$ and $d_{ii} = 0$. The mean of relative distances for each x_i to all other scores x_j is calculated as

$$\bar{d}_i = \sum_{j=1}^{n} d_{ij} f_j \Big/ \left(\sum_{j=1}^{n} f_j \right) - 1 \quad (6)$$

This average of relative distance $\bar{d}_i$ measures the proximity of x_i to the centre of the values. Clearly, a smaller $\bar{d}_i$ implies x_i is closer to the centre, and thus x_i will be assigned with a higher weight during the calculation of mode m. To define the weight of x_i, a pairwise comparison between x_i and x_j is computed based on their average distances as

$$r_{ij} = \bar{d}_i / \bar{d}_j \quad (7)$$

Next, a pairwise comparison matrix $\mathbf{R} = [r_{ij}]_{n \times n}$ is defined, where r_{ij} is the relative importance of x_i compared to x_j, and this implies $r_{ij} = 1/r_{ji}$ and $r_{ii} = 1$. We now need to calculate the weight of x_i based on its pairwise comparison to any other score x_j. Since $\mathbf{R}$ is achieved from pairwise distance comparison calculations, it is truly consistent, that is, there exists a coherent judgement in determining the pairwise comparison of the weight of x_i. Suppose w_i be the actual weight of x_i and has a value of [0,1]. Due to the consistency of $\mathbf{R}$, we are able to define r_{ij} in (7) as

$$r_{ij} = \frac{w_i}{w_j}, \quad \forall i, j \quad (8)$$

Further, we establish $\mathbf{w}$ as a column vector of w_i, and from (8) we can define

$$\mathbf{R}\mathbf{w} = n\mathbf{w} \quad (9)$$

TABLE 2. An illustrative of a frequency distribution of the normalized mean (G) of a hypothetical contact dataset.

Interval (G)	0.0-0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1.0
Crisp value (x_i)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Freq. (f_i)	39	19	35	47	10	75	45	83	106	191

where n and $\mathbf{w}$ are an eigenvalue and eigenvector of $\mathbf{R}$, respectively. Moreover, given that $\sum_{i=1}^{n} w_i = 1$, $\mathbf{w}$ is then solved, where the weight of x_i is calculated as follows

$$w_i = \frac{1}{\sum_{j=1}^{n} r_{ji}}, \quad i = 1, \ldots, n \tag{10}$$

with w_i represents the significant degree of x_i in the calculation of the mode m. Finally, the mode m of the TFN is defined as

$$m = \sum_{i=1}^{n} w_i x_i \tag{11}$$

After obtaining the mode m, we now need to compute the spreads of the fuzzy number, that is the left (a) and right (b) endpoints of the TFN. The calculation initially requires the knowledge of deviation (σ) of the fuzzy number. From [25], the mean deviation of a TFN (a, m, b) is typically calculated as

$$\sigma = \frac{\int_a^b |x - m| \cdot \mu_F(x)\, dx}{\int_a^b \mu_F(x)\, dx} \tag{12}$$

For $\mu_F(x)$ be a triangular membership function, (12) can be solved as

$$\sigma = \frac{(m-a)^2 + (b-m)^2}{3(b-a)} \tag{13}$$

Let φ be the fraction between the left and right spreads as

$$\varphi = \frac{m-a}{b-m} \tag{14}$$

From (13) and (14), the left (a) and right (b) endpoints of the TFN are solved as

$$a = m - \frac{3(1+\varphi)\varphi\sigma}{1+\varphi^2} \tag{15}$$

$$b = m + \frac{3(1+\varphi)\sigma}{1+\varphi^2} \tag{16}$$

To calculate a and b, both σ and φ are required to be known at first. An approximation strategy is then used to solve these parameters. Firstly, to approximate σ, a mean deviation s is computed from the given scores x_i and their respective weights w_i as

$$\sigma \approx s = \sum_{i=1}^{n} w_i |x_i - m| \tag{17}$$

Secondly, φ is calculated as follows: to approximate the left (a) and right (b) endpoints of the TFN, we initially define x^l and x^r be the weighted mean of the scores x_i that are below and above m, respectively, at the α– cut (see Fig. 4). Moreover, let

$$M^- = \{i | x_i < m, i \in I\}$$

and

$$M^+ = \{i | x_i > m, i \in I\}$$

for $I = \{1, \ldots, n\}$, the computation of x^l and x^r are given as

$$x^l = \frac{\sum_{i \in M^-} w_i x_i}{\sum_{i \in M^-} w_i} \tag{18}$$

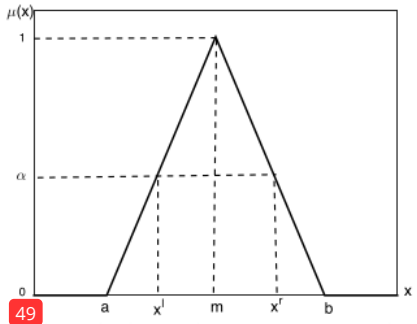

FIGURE 4. The left and right spreads of a TFN (a, m, b) at α-level.

$$x^r = \frac{\sum_{i \in M^+} w_i x_i}{\sum_{i \in M^+} w_i} \tag{19}$$

since x^l and x^r are defined at the same α–level, from (14) φ can be approximated as

$$\hat{\varphi} = \frac{m - x^l}{x^r - m} \tag{20}$$

Finally, we apply the proposed membership function elicitation method on realistic node mobility scenarios. In the present study, we consider two real human contact datasets, namely Haggle [47] and Reality [48], which represent the short-term and long-term human behaviours in their social environments, respectively. The Haggle dataset recorded the contact events of 41 participants of the 2005 Infocomm conference lasted for 3 days in Miami, USA. However, the Reality trace captured the mobility of 97 students and staffs in the MIT campus during an academic year. In general, our proposed method works in any human mobility model as long as the node contacts follow certain probability distributions reflecting their social relationships. However, this is not the case for catastrophe or disaster scenarios, where human movements are sporadic and frequently random [49].

To build TFNs for the FRIMF's fuzzy parameters (G and B), we firstly need to know the frequency distributions of the normalized mean and burstiness variation of pairwise intercontact times, respectively, for each contact dataset. Using a data mining technique, we gather information of pairwise intercontact times from all nodes across the given dataset. Using this knowledge, we calculate the burstiness metric (B) and the normalized mean (G) for each pair of nodes in the dataset using (1) and (2), respectively. Afterwards, we construct Table 2 for each parameter by initially defining the bin interval and next counting how many values fall into each bin. After the binning process, we portray the frequency distributions of the discrete (crisp) values of G_i and B_i for Haggle and Reality in Figs. 5 and 6, respectively (in this case, we use the bin interval of 0.1 for both G and B distributions).

From Figs. 5 (left) and 6 (left), we notice that both the datasets exhibit almost a similar characteristic in terms of the statistical mean distribution. Particularly, the number of nodes having a high normalized mean of intercontact times with their peers is large in both the datasets. In other words,

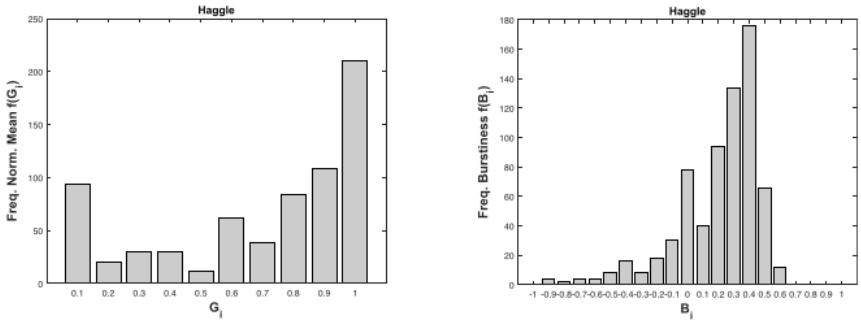

FIGURE 5. Frequency distributions of the discrete (crisp) values of the normalized mean (G) and burstiness parameter (B) of pairwise intercontact times in the Haggle dataset.

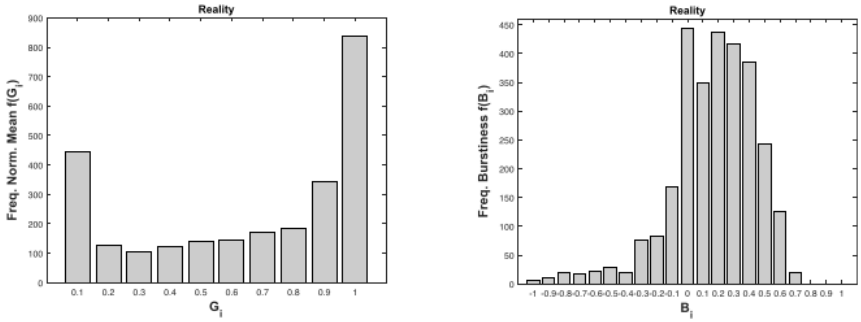

FIGURE 6. Frequency distributions of the discrete (crisp) values of the normalized mean (G) and burstiness parameter (B) of pairwise intercontact times in the Reality dataset.

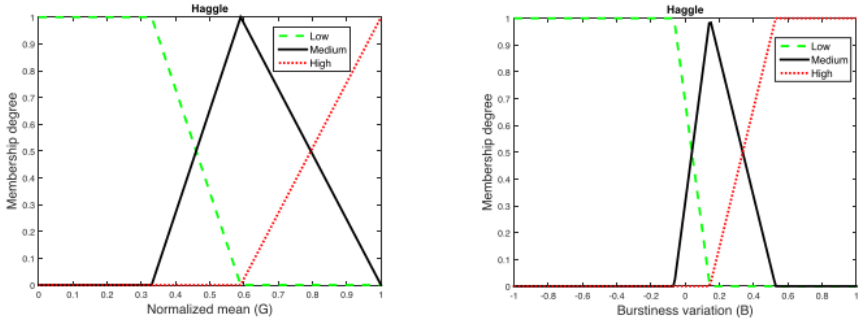

FIGURE 7. Asymmetric TFNs of the FRIMF's fuzzy parameters: normalized mean (G) and burstiness variation (B) in the Haggle dataset.

in both the mobility scenarios many individuals have very close relationships with their mates/colleagues (shown by a high value of G or a low average intercontact time). However, if we notice the frequency distributions of the burstiness variation in Haggle and Reality in Figs. 5 (right) and 6 (right), respectively, it is clear that the contact events possess a bursty nature, indicated by the majority of B values are larger than zero. This also agrees with the work in [11] that confirmed the bursty characteristic in the interevent distribution in human dynamics.

Based on the frequency distributions of the normalized mean and the burstiness variation of pairwise intercontact times in Figs. 5 and 6, we construct TFNs for both G and B in Haggle and Reality, respectively. We use the estimation method that exploits the weight determination technique of (6)-(20) to calculate the mode (m) and the spreads (a, b) of the TFN for G and B for each contact dataset. Finally, we show the obtained asymmetric TFNs (in solid black lines) for G and B in Figs. 7 and 8 for Haggle and Reality, respectively. These TFNs are fuzzy sets that represent the (graded) possibility distributions of G and B in the given dataset. We next categorize these TFNs as the fuzzy set of a medium (or ordinary) class. Given that we defined three classes for each FRIMF's fuzzy system input (low, medium, and high) in the previous section, we now need to create the remaining ones. We determine the fuzzy sets for the low and high classes using the definition in [41], as follows. Let S_i and S_{i+1} be adjoining two fuzzy sets with an overlapped area (where S_i

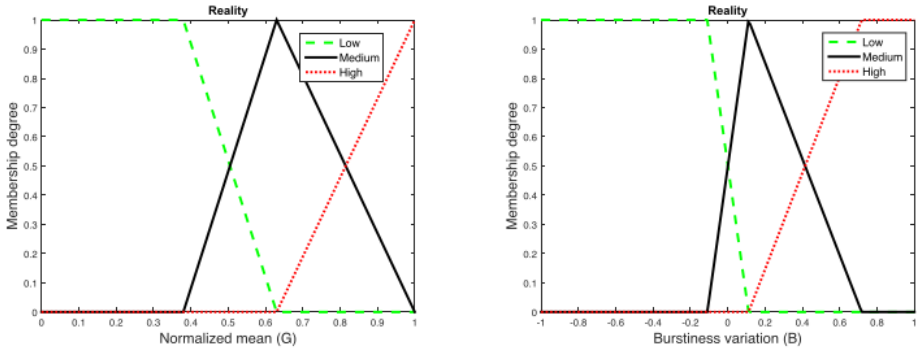

FIGURE 8. Asymmetric TFNs of the FRIMF's fuzzy parameters: normalized mean (*G*) and burstiness variation (*B*) in the Reality dataset.

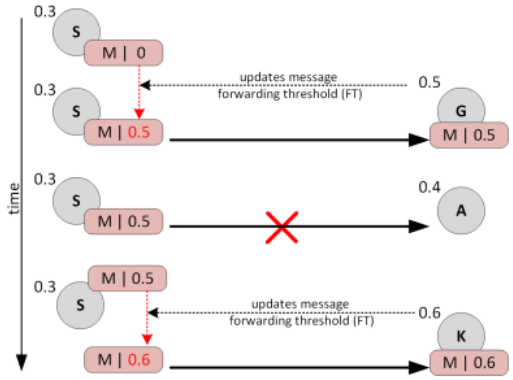

FIGURE 9. A brief scenario of delegation forwarding.

and S_{i+1} are defined in the real number $\Re$). Therefore, for $\forall x \in S_i \cap S_{i+1}$,

$$\mu_i(x) + \mu_{i+1}(x) = 1 \tag{21}$$

holds, where $\mu_i(x)$ and $\mu_{i+1}(x)$ represents the membership degree of a variable x in the fuzzy sets i and $i+1$, respectively. Since the fuzzy set of the medium class has already been known, we can easily define the fuzzy sets of the low and high classes using (21). As a result, we show the attained fuzzy sets of the low (in green dashed lines) and high (in red dotted lines) classes for both *G* and *B* in Figs. 7 and 8 for Haggle and Reality, respectively. In Section IV.1., we will examine the delivery performance of FRIMF using the typical symmetric TFNs in Fig. 2 compared to that of FRIMF utilizing the enhanced asymmetric TFNs in Figs. 7 and 8 for Haggle and Reality, respectively.

C. CONSTRUCTION OF THE FRIMF FORWARDING STRATEGY

We now arrive at the final part of designing the FRIMF routing algorithm. Here, we discuss how a message is relayed hop-by-hop from the source to the destination effectively. To achieve this goal, a hill-climbing heuristic search is applied, where in each hop the routing algorithm greedily maximizes the utility function (i.e., the closeness to the destination) based on the node's local knowledge. That is, when a contact occurs, the current node *A* calculates its closeness value to the destination *D*, and forwards its (copy) message to the peer *B* only when the *B*'s closeness value is higher than *A*'s ($C_{B,D} > C_{A,D}$). Furthermore, to improve the heuristic routing performance, we add two properties in the forwarding decisions, namely social transitivity [50] and delegation forwarding [51].

Firstly, we exploit the transitive property of social networks to increase the message delivery likelihood in the network. When node *A* has a strong relationship with node *B*, and *B* has a high correlation with *D*, then *A* is more likely to be a good relay of messages destined for *D*. Equation (22) below shows how the transitivity now affecting the calculation of the closeness of *A* towards *D*, with $\beta \in [0, 1]$ controls the impact of transitivity in the overall computation.

$$C_{A,D} = C_{A,D} + \left(1 - C_{A,D}\right).C_{A,B}.C_{B,D}.\beta \tag{22}$$

Secondly, to decrease the number of message copies distributed in the network, we apply the delegation forwarding (DF) [51] on the FRIMF's routing decisions. DF implements the optimal stopping theorem from the probability theory. We briefly discuss how DF works based on a simple scenario in Fig. 9, as follows. Node *S* (source) initially produces a new message *M* with the forwarding threshold (*FT*) is set to "0". During its mobility, *S* meets node *G*. Since the *G*'s closeness value ($C_{G,D} = 0.5$) is higher than *S*'s ($C_{S,D} = 0.3$), *S* then updates the *M*'s *FT* value with the *G*'s closeness value and promptly sends a copy of *M* to *G*. In the subsequent contact, *S* encounters *A* whose closeness value ($C_{A,D} = 0.4$) is higher than that of *S*. However, *S* does not forward the message to *A*, since the *A*'s closeness value is lower than the *FT* value of *M*. Lastly, *S* has a contact with node *K* whose closeness value ($C_{K,D} = 0.6$) is higher than both the *S*'s closeness value and the *M*'s forwarding threshold. *S* then updates the *M*'s *FT* value with the *K*'s closeness value and transfers the message to *K*.

To summarize how FRIMF works, we construct Algorithm-1 to describe our proposed scheme

in detail.[1] During the warm-up time, each node in the network records its contact history with its peer nodes. When the training phase terminates, the node calculates the normalized mean (G) and the burstiness variation (B) for each previously contacted node. Through the fuzzy evaluation system in Fig. 1 and also considering the given TFNs for both FRIMF's parameters in the particular contact dataset, the node infers its closeness degree to each peer. During the forwarding phase, when a contact occurs, the node computes its closeness value to the (message) destination using (22), and then exchanges this value to the encountered node. When the peer's closeness value is higher than both the current node's closeness value and the message's forwarding threshold value, the current node promptly replicates the message to the peer.

Algorithm 1 The FRIMF Forwarding Scheme (Node A)

Input: TFN_G, TFN_B for the given contact dataset
The warm-up phase:
Begin
  collect enough information about the pairwise intercontact times with all peers;
  For (each peer) **do**
    compute $G_{A,peer}$ and $B_{A,peer}$;
    compute $C_{A,peer}$ = fuzzy ($G_{A,peer}$, TFN_G, $B_{A,peer}$, TFN_B);
  End for
End
The message forwarding phase:
when a contact occurs with node B, and A decides to forward a message M destined for D;
Begin
  send $C_{A,D}$;
  receive $C_{B,D}$;
  update $C_{A,D}$ based on the knowledge of $C_{B,D}$;
  If $((C_{B,D} > C_{A,D}) \wedge (C_{B,D} > FT_M))$ **then**
    update FT_M with $C_{B,D}$;
    sends a copy of M to the peer B;
  End if
End

IV. SIMULATION RESULTS AND DISCUSSION

A. PERFORMANCE EVALUATION OF THE FRIMF ALGORITHM

This section focuses on comparing the delivery performance of FRIMF when the routing parameters are fuzzified using the symmetric TFNs in Fig. 2 to that when the parameters are fuzzified using the asymmetric TFNs in Figs. 7 or 8, depending on the chosen contact dataset. For simulations, we adopt the ONE simulator [27] and real human mobility scenarios, namely Haggle [47] and Reality [48]. In these simulations, the number of nodes and the duration of simulation time vary depending on the mobility settings: we use 41 nodes with the simulation time of 3 days for Haggle, but for Reality we consider 97 nodes with the simulation period of 16 weeks. In order to provide an opportunity for nodes to gather the information of pairwise intercontact times with all the peers in the network, 30 percent of the simulation time is used as a warm-up phase. The buffer size of nodes and the size of messages are set to 20MB and 10kB, respectively. Each node generates messages to uniformly, randomly chosen destinations at a rate of 3 messages per hour for all scenarios, and for each new created message the time-to-live (TTL) is set to 6 hours and 1 week for Haggle and Reality, respectively. Finally, we concentrate on the following evaluation metrics for FRIMF's performance analysis:

- Delivery ratio: the fraction of total delivered messages to the number of messages created during the simulation time.
- Average latency: the mean time from the creation of a message in the source until the forwarding it to the destination.
- Overhead ratio: the cost to successfully transfer a message to the destination, calculated as the total forwarded (message) copies divided by the total delivered messages.
- Total forwards: the total number of replicas created and forwarded during the node contacts throughout the simulation time.

Before we investigate the delivery performance of FRIMF, we firstly discuss the characteristic of closeness (C) as the output of the FRIMF's Mamdani fuzzy inference system with two different input variables: normalized mean (G) and burstiness variation (B). Using the MATLAB's function gensurf, we portray the output surface of closeness in Fig. 10 for two distinct cases: the first one is FRIMF when the input parameters are fuzzified using the typical symmetric TFNs in Fig. 2 (hereafter, we refer to this as *symmetric–TFN*), and the other one is that when the fuzzification uses the improved asymmetric TFNs in Figs. 7 and 8 for Haggle and Reality, respectively (hereafter, we call this *asymmetric–TFN*). From Fig. 10, we notice that in the case of asymmetric–TFNs, the closeness (C) is very low and is insensitive with the change of burstiness variation (B) when the normalized mean (G) is less than 0.4 in both mobility scenarios. However, for all the cases (both symmetric–TFN and asymmetric–TFN), the closeness reaches its highest value when the normalized mean is high and the burstiness variation is low ($B < 0$). In other words, the tie strength between two nodes is high whenever the average separation time between consecutive contacts is low (indicated by a high value of G) and the contacts follow a more regular pattern (represented by a negative value of B). Subsequently, the impact of considering symmetric and asymmetric TFNs in the calculation of closeness (C) is investigated in terms of FRIMF's delivery performances, as follows.

We discuss the performance of FRIMF according to the provided evaluation metrics. In Figs. 11 and 12, we plot the delivery performance changes of symmetric–TFN versus asymmetric–TFN as the number of node contacts increase in Haggle and Reality, respectively. From the figures, we observe almost similar performances of both schemes

[1]For the detail implementation of FRIMF in the ONE simulator, please refer to https://github.com/soelistijanto/FRIMF

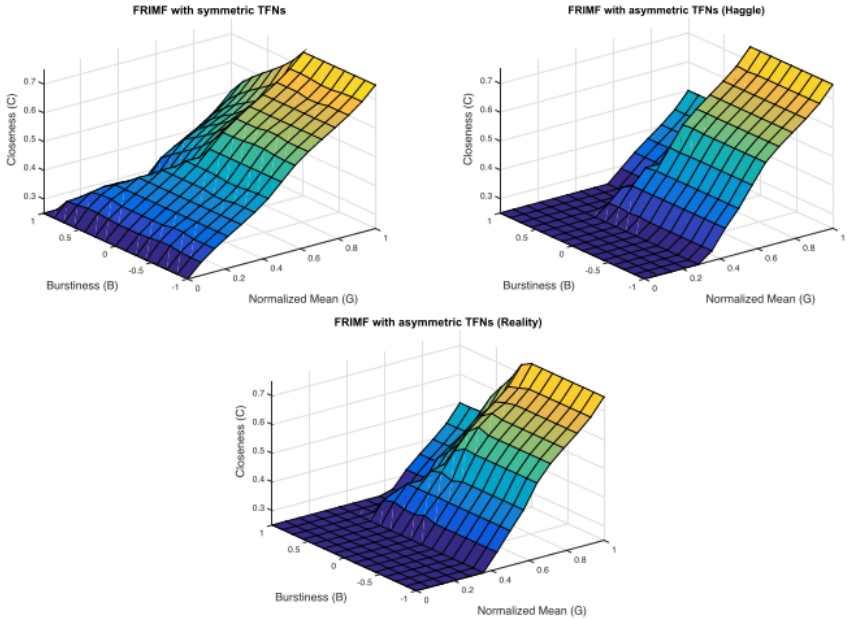

FIGURE 10. Output surfaces of closeness (*C*) derived from the FRIMF's Mamdani fuzzy inference system with two input variables: normalized mean (*G*) and burstiness variation (*B*), for two different cases: symmetric and asymmetric TFNs (Haggle and Reality).

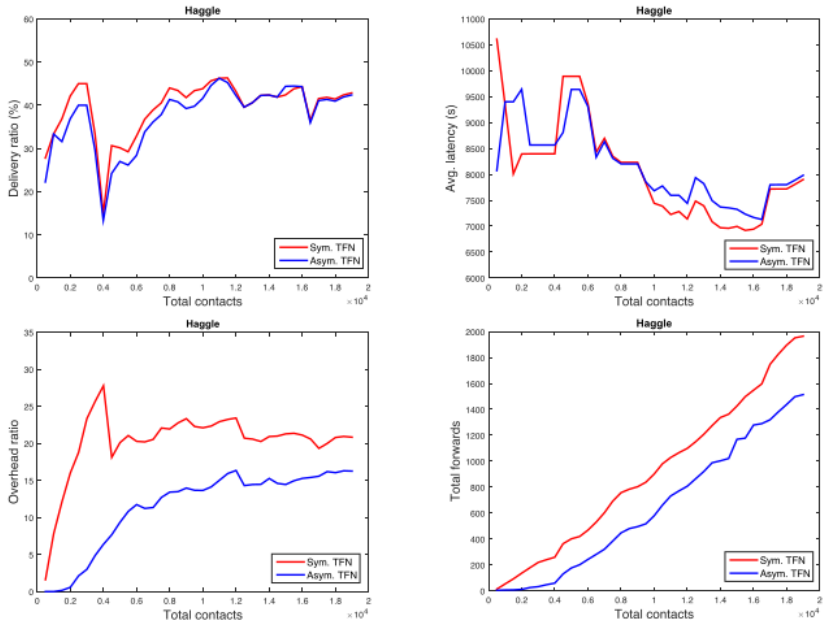

FIGURE 11. Delivery performances of FRIMF, comparing symmetric-TFN and asymmetric-TFN in four evaluation metrics in Haggle.

in terms of delivery ratio and average latency in the given mobility scenarios. In Haggle, both symmetric–TFN and asymmetric–TFN are able to deliver the messages to the destinations in about the same success rate; yet, asymmetric–TFN performs somewhat better in Reality. Additionally, we also see slight variations in the delivery latency of the two schemes in both mobility schemes, suggesting that both of them are able to maintain roughly a similar delivery time. In contrast, we notice clear performance differences between symmetric–TFN and asymmetric–TFN in terms of delivery cost, evaluated in overhead ratio and total forwards, in both Haggle and Reality. In this case, asymmetric–TFN can significantly

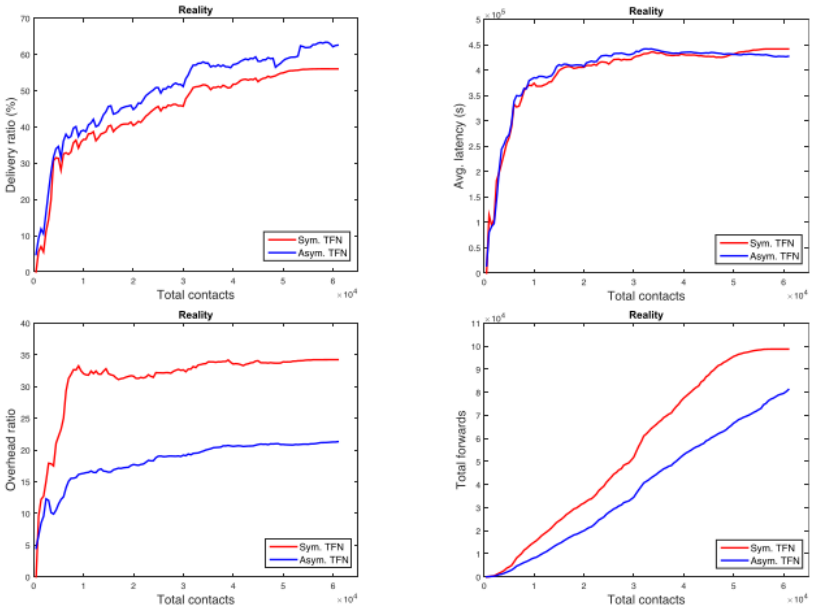

FIGURE 12. Delivery performances of FRIMF, comparing symmetric-TFN and asymmetric-TFN in four evaluation metrics in Reality.

reduce the number of copies forwarded during the node contacts, indicated by a lower total forwards. With the low number of forwards combined with a delivery ratio that is as high as that of symmetric–TFN, asymmetric–TFN is thus superior to symmetric–TFN in the overhead ratio performance. This demonstrates the effectiveness of FRIMF with asymmetric TFNs in transmitting messages to the intended recipients. Thanks to the improved asymmetric TFNs, the routing algorithm carefully selects a small number of optimal carriers that can quickly transfer the messages to the final targets. To sum up the discussion, Table 3 compares the benefits and drawbacks of the subjective approach with those of the objective technique for developing membership functions for the FRIMF fuzzy parameters.

B. COMPARING FRIMF WITH OTHER ALGORITHMS

In this section, we benchmark FRIMF against other OMN routing schemes. For this purpose, we consider Prophet [31], FuzzyCom [52] and Epidemic [53]. We choose Prophet because of several reasons, as follows: first, Prophet is a classical, but prominent probabilistic routing scheme for OMNs; second, both Prophet and FRIMF use a single routing metric derived from contact statistics to define the connection strength between a pair of nodes; finally, we need a fair performance comparison between routing decisions based on probability measures (Prophet) and those based on fuzzy terms (FRIMF). Subsequently, to have a reasonable benchmark with other fuzzy routing algorithms, we select FuzzyCom for the following reasons: first, like FRIMF, FuzzyCom merely uses encounter data as the input variables of the fuzzy inference system; second, while FRIMF only takes into account a single contact metric, namely intercontact times, to determine the closeness degree of a pair of nodes, FuzzyCom considers a number of contact metrics, including frequency contact, intercontact times, and longest contact separation; thus, we can investigate the performance differences of utilizing one contact metric against using numerous contact metrics; third, FuzzyCom ignores the contact information when defining the membership functions and simply uses symmetric TFNs for its routing metrics (subjective approach), while FRIMF uses asymmetric TFNs derived from the statistical distributions of intercontact times (objective method); finally, both FuzzyCom and FRIMF apply delegation forwarding (DF) in order to reduce the replicas forwarded during the node contacts. Lastly, in addition to Prophet and FuzzyCom, we also consider the flooding-based strategy Epidemic as the benchmark, since theoretically it has the best performance in terms of delivery ratio and latency when the network resources are supposed to be unlimited.

We now discuss the delivery performance of FRIMF compared with that of the given benchmarks in the Haggle and Reality scenarios. For FRIMF, we only consider in the case of asymmetric–TFN. For simulations, we use the ONE simulator with the simulation settings similar to those in the previous section. For each algorithm, we run the simulations 5 times with different random seeds for both mobility scenarios. We eventually present in Figs. 13 and 14, for Haggle and Reality, respectively, the delivery performances of FRIMF and its benchmarks evaluated in the given evaluation metrics. In terms of delivery ratio, we see that FRIMF can maintain performance levels that are fairly comparable to those of Prophet and FuzzyCom in both scenarios, whereas

TABLE 3. Pros and cons of the subjective approach vs. the objective approach of the membership function elicitation methods in FRIMF.

	Subjective approach (symmetric-TFN)	Objective approach (asymmetric-TFN)
Methods	simple, straightforward	using mathematical procedures
Required prior knowledge	our assumptions/subjective preferences	statistical distributions of the pairwise intercontact times
Challenges in real-life OMN settings	no/less effort	a non-trivial task in collecting pairwise contact data from all the mobile nodes
Routing performances	less efficient (a larger number of forwards)	more efficient (fewer created replicas)

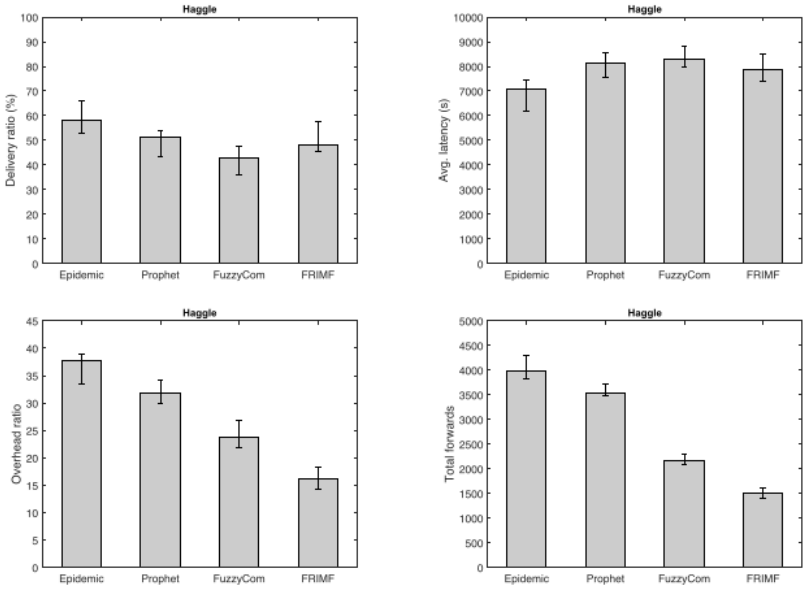

FIGURE 13. Delivery performances of FRIMF compared with those of the given benchmarks in four evaluation metrics in Haggle.

Epidemic excels in this performance metric (yet, Epidemic as a flooding-based strategy never achieves its ideal performance of 100% success rate in these circumstances due to the restricted resources of the network nodes). However, heuristic-based routing techniques, such as Prophet, FuzzyCom, and FRIMF, are capable of successfully delivering the messages with a probability that is close to that of Epidemic.

Furthermore, FRIMF performs better than Prophet and FuzzyCom in terms of delivery delay in Haggle; yet, in Reality FRIMF slightly increases the delivery times beyond those of Epidemic and Prophet. However, FRIMF outperforms all the benchmarks in terms of delivery cost, as determined by the overhead ratio and total forwards. FRIMF produces the fewest total copies forwarded during node interactions while maintaining the delivery success rate at levels that are somewhat similar to the benchmarks. As a result, FRIMF retains the lowest overhead ratio in both scenarios. In particular, when contrasted with Prophet, this shows that the fuzzy-based routing decisions of FRIMF are superior to the probabilistic routing decisions made by Prophet. This implies that the FRIMF's fuzzy inferences are more effective than the Prophet's probabilistic estimates at determining the strength of pair connections, thus enabling FRIMF to choose fewer optimal carriers for a given destination. Finally, the use of DF to lower the number of replicas has a little impact on the FRIMF's overall delivery performances, as it can keep both the delivery ratio and delay that are on par with those of Prophet.

Finally, when compared to FuzzyCom, the superior performance of FRIMF can be analyzed in several viewpoints, as follows. First, it demonstrates that a single contact metric, namely intercontact times, which is used by FRIMF, can outperform multiple encounter metrics used by FuzzyCom in defining the connection strength between a pair of nodes. This is further supported by the findings in [29] and [30] which showed that intercontact times can surpass both duration and frequency contacts in assessing the dynamics of human relations in OMNs. Second, opposed to FuzzyCom, which uses the symmetric TFNs to fuzzify its routing parameters, FRIMF can more effectively transport the messages to the destinations thanks to the use of the asymmetric TFNs developed based on the contact information. This again verifies that the objective strategy of developing membership functions for the routing parameters indeed improves the delivery

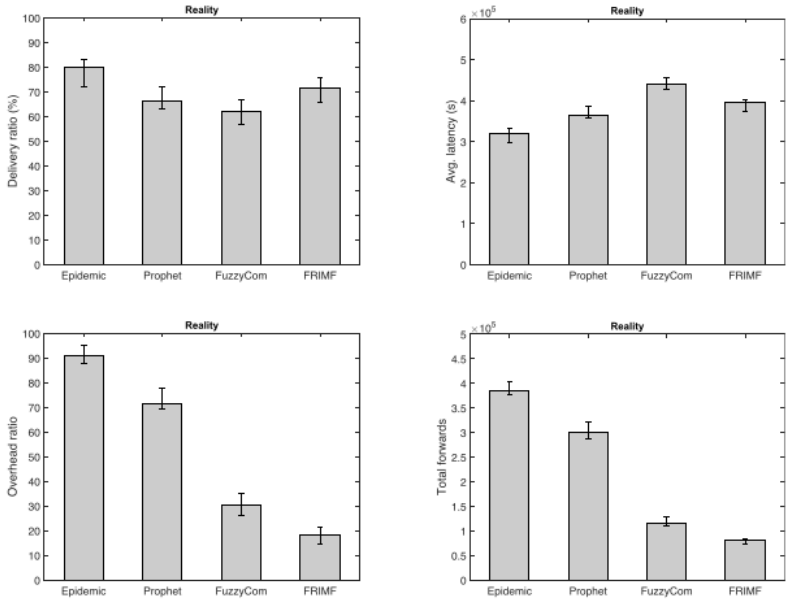

FIGURE 14. Delivery performances of FRIMF compared with those of the given benchmarks in four evaluation metrics in Reality.

performance of OMN fuzzy routing algorithms. Lastly, it is evident that the usage of delegation forwarding (DF) in FuzzyCom and FRIMF can reduce the total forwards below those of Epidemic and Prophet. Nevertheless, this considerable drop in delivery cost has less of an impact on FRIMF, allowing it to rise the delivery ratio and latency performances beyond those of FuzzyCom.

V. CONCLUSION

The fuzzy routing scheme called FRIMF was proposed in this paper. It takes advantage of node closeness to select the most suitable message carriers for a particular destination. A fuzzy inference system was used to determine the strength of a pair connection based on the normalized mean and the burstiness variation of pairwise intercontact times. In order to enhance the transmission environment, we further developed a method to create optimal membership functions for the FRIMF's fuzzy parameters based on the statistical distributions of pairwise intercontact times. Eventually, asymmetric TFNs were obtained, and these functions were then employed to properly characterize the fuzzy sets of the FRIMF parameters. Simulation results, which were based on the real human contact traces, showed that the asymmetric TFNs can improve the delivery performance of FRIMF with the typical symmetric TFNs defined based on our subjective preferences. Finally, FRIMF outperformed all the given algorithm benchmarks, in terms of delivery cost and latency.

ACKNOWLEDGMENT

The Author would like to thank his student Afra Rian Yudianto, for providing the Java codes of FRIMF in the ONE simulator.

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